Food and Agriculture Organization of the United Nations

REGIONAL ASSESSMENT OF ABOVE-GROUND BIOMASS USING FIELD, AIRBORNE LIGHT DETECTION AND RANGING AND SATELLITE DATA INTEGRATION

Methodological document

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REGIONAL ASSESSMENT OF ABOVE-GROUND BIOMASS USING FIELD, AIRBORNE LIGHT DETECTION AND RANGING AND SATELLITE DATA INTEGRATION

Methodological document

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Food and Agriculture Organization of the United Nations
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CONTENTS

Acknowledgements IV

Introduction **1**

Methodology **4**

2.1. Field data collection 5
2.2. Unmanned aerial vehicle laser scanning data collection 11
2.3. GEDI waveform simulation and modelling 12
2.4. Inference 14

Results **16**

Discussion **20**

Data records 23
References 24

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It describes the methodology to estimate above-ground biomass in the West Africa subregion, as part of project activities to generate new forest data to cover critical gaps on forest status and dynamics (project output 1.1). The methodology has been developed and implemented through a collaboration between FAO, the Forestry Research Institute of Ghana (FORIG), the University of Oxford and the University of Maryland.

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ABBREVIATIONS

AGBD	above-ground biomass density
ALS	airborne Laser scanning
CWD	coarse woody debris
DBT	deciduous broadleaf trees
EBT	evergreen broadleaf trees
FAO	Food and Agriculture Organization of the United Nations
FORIG	Forestry Research Institute of Ghana
FSBD	Forest Structure and Biomass Database
GEDI	Global Ecosystem Dynamics Investigation
GEM	Global Ecosystem Monitoring
GHMB	generalized hierarchical model-based
GNSS	global navigation satellite system
INS	inertial navigation system
L4	Level 4
LiDAR	light detection and ranging
NFI	National Forest Inventory
PFT	plant functional type
PSPs	permanent sampling plots
RAINFOR	Red Amazónica de Inventarios Forestales
REDD+	Reducing Emissions from Deforestation and Forest Degradation, plus sustainable forest management, conservation and enhancement of forest carbon stocks
RMSE	root mean square error
SAR	synthetic aperture radar
UAV	unmanned aerial vehicle
UAV-LS	unmanned aerial vehicle – LiDAR system

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INTRODUCTION

Tropical forests are highly diverse and contribute substantially to the global carbon budget (Friedlingstein *et al.*, 2025). Despite their importance, tropical forests are under intense threat from deforestation and degradation, which contribute substantially to anthropogenic emissions of greenhouse gases (Pan *et al.*, 2011). For this reason, countries with tropical forests, including the West African subregion, could benefit from incentives designed to help reduce emissions from deforestation and forest degradation, plus sustainable forest management, conservation and carbon stock enhancement (REDD+), an initiative under the United Nations Framework Convention on Climate Change (IPCC, 2006; Sanz & Penman, 2016).

Accurate estimates of above-ground biomass density (AGBD) are essential for understanding forest carbon stocks and informing climate mitigation efforts (Houghton, 2005; van Breugel *et al.,* 2011; Santoro *et al.*, 2021; Tian *et al.*, 2022; Friedlingstein *et al.*, 2025). Ground-based forest inventories are essential for assessing forest biomass carbon stocks, determining emission factors for greenhouse gas reporting and validating remote sensing data (Baker, 2013). While the number of countries conducting national and subnational forest inventories (NFIs) has grown globally, significant gaps persist — particularly across Africa (Gillerot *et al*., 2021; Nesha *et al.*, 2022). Only a few countries in the region have implemented NFIs, limiting the calibration and validation of country-scale maps, despite their critical role in national policy- and decision-making (Gaston, 1998; Roberts *et al.*, 2023).

Recently, there has been a high level of interest in measuring the quantity of carbon in tropical forests in order to access carbon credits through the REDD+ initiative, but this shortage of ground-based AGBD data also in many regions limits the calibration of country-scale maps and undermines robust climate reporting under mechanisms such as REDD+, including submissions to the United Nations Framework Convention on Climate Change, the Forest Carbon Partnership Facility and the Architecture for REDD+ Transactions — The REDD+ Environmental Excellence Standard (Gibbs, 2007; Butler *et al.*, 2024). Addressing these gaps is crucial for improving the forest resource assessments and strengthening national and regional climate policies (Baker *et al.*, 2010; MacDicken, 2015).

Hybrid approaches that integrate remote sensing with field measurements offer a promising solution (Eisfelder, Kunzer & Dech, 2012; Réjou-Méchain *et al.*, 2019). Model-assisted and model-based techniques leverage remote sensing data to enhance the precision, coverage and reliability of AGBD estimates (McRoberts *et al.*, 2014; Chen *et al.*, 2016; Lu *et al.*, 2016; Papucci *et al.*, forthcoming). These approaches not only reduce uncertainties but also support better-informed climate policies and resource management strategies (Ene *et al*., 2012; Lu *et al.*, 2016; Herold *et al.,* 2019; GFOI 2020; Ma *et al.*, 2024).

Two crucial factors warrant attention in the current state of the art in national-scale AGBD estimation. First, the reliability of manual survey protocols is a significant concern, as inconsistencies in data collection methods and observer bias can introduce errors in ground-based measurements. Second, the spatial overlap between ground plots and remote sensing pixels can lead to discrepancies in biomass estimates, potentially affecting the integration of field data with remotely sensed observations (Ma *et al.,* 2024). Addressing these challenges is vital for improving the robustness of AGBD assessments and ensuring that the derived estimates accurately reflect forest carbon stocks. Additionally, uncertainties may arise from various sources, including the

quality and resolution of remote sensing imagery, variability in sampling plot survey data, stand structural complexity and limitations in statistical models used for biomass estimation (Tian *et al*., 2022). Recognizing and addressing these uncertainties is essential for improving the robustness of AGBD assessments and ensuring that the derived estimates accurately reflect forest carbon stocks.

Several international initiatives are advancing AGBD estimation through remote sensing (Tian *et al.*, 2022; Khan *et al.* 2025). The European Space Agency's BIOMASS mission, for example, utilizes P-band synthetic aperture radar (SAR) to provide global biomass estimates, complementing light detection and ranging (LiDAR)-based measurements, like those from NASA's Global Ecosystem Dynamics Investigation (GEDI) (Quegan *et al.*, 2019; Dubayah *et al.*, 2023). Similarly, NASA's ICESat-2 and NASA-ISRO SAR missions contribute critical data for the monitoring of forest structure and biomass dynamics (Silva *et al.*, 2021). These efforts, alongside national and regional programmes (e.g. Fischer *et al*., 2024; Hunka *et al*., 2025) enhance large-scale AGBD mapping and support climate reporting (Langner, Achard & Grassi, 2014). GEDI's waveform footprints (25 m diameter) enable vegetation structure analysis and AGBD mapping at large scales with the support of field data through calibration and validation procedures (Herold *et al.,* 2019; Duncanson *et al.,* 2022). These can provide useful insights on the additionality of modelling carbon budgets (Duncanson *et al.*, 2023) and understanding how vegetation structure affects habitat quality and biodiversity (Valbuena *et al.*, 2020).

In Africa, the availability of NFIs remains uneven, with pronounced disparities across subregions (Brown & Gaston 1995; Mayaux, Achard & Malingreau, 1998; Akande 2014; MacDicken, 2015; Asiyanbi, Arhin & Isyaku, 2017; Gizachew *et al.*, 2017). West Africa exemplifies these challenges: Fewer than 30 percent of countries have implemented NFIs or have reliable ground-based AGBD data, and a recent Food and Agriculture Organization of the United Nations (FAO) assessment of 14 Economic Community of West African States countries revealed critical gaps — particularly in Guinea and Niger — where forest inventory metrics (e.g. carbon pools, soil carbon data) are missing or outdated (Roberts *et al.,* 2023). Further, existing forest data are spatially fragmented, and regionally applicable allometric equations are scarce (Henry *et al.,* 2010; Aabeyir *et al.*, 2020; Valbuena *et al.*, 2016). This results in highly uncertain emission factors and undermines climate reporting.

Only a handful of countries have collected inventory data in the past decade, and none have conducted more than one NFI in 20 years, undermining their ability to access climate finance or report under international mechanisms. To benefit from these incentives, West African countries wishing to undertake REDD+ need to demonstrate that they have reduced carbon emissions. This requires the design and implementation of robust national forest monitoring systems, using a combination of forest inventories and remote sensing. Finally, capacity constraints further exacerbate these issues: While stakeholders are familiar with basic inventory tools (e.g. diameter at breast height tapes), few have training in digital data collection, carbon assessment methods, or geospatial analysis — key skills for robust measurement, reporting and verification systems. To address these gaps, FAO launched the "Global Transformation of Forests for People and Climate: A focus on West Africa" project aimed at building a consistent national and regional dataset of West Africa carbon stocks that have been tested and harmonized through replicable methodology that leverages GEDI footprints of LiDAR pulses calibrated using field plot data and airborne laser

scanning (ALS) from unmanned aerial vehicle (UAV) flights, hereafter referred to as UAV laser scanning (UAV-LS). The methodology was developed and implemented in collaboration with three international partners: the Forestry Research Institute of Ghana (FORIG) carrying out the field campaign, the University of Oxford for the UAV-LS flights and the University of Maryland in charge of integrating plot information to calibrate and validate GEDI data. The field campaign focused on 37 field plots in Ghana, where corresponding UAV-LS flights were conducted, allowing for the refinement of GEDI-based AGBD estimates. These calibrated estimates serve as a foundation for producing both national and regional AGBD maps across West Africa, contributing to a broader understanding of biomass distribution in the region.

The objective of this document is to describe the methodology that was conducive to generating data on above-ground biomass at the West Africa subregional level, as well as to highlight its replicability in other countries and regions.

METHODOLOGY

To address the scarcity of reliable AGBD data in West Africa, the project employed an integrated approach combining field plot measurements, UAV-LS, and spaceborne GEDI LiDAR data. The methodology was designed to **(1)** calibrate and validate GEDI-derived biomass models using field and UAV-LS data to ensure regional applicability, **(2)** extend spatially continuous AGBD estimates across West Africa by leveraging GEDI's systematic sampling, and **(3)** reduce uncertainties through multisource data fusion. GEDI's preexisting biomass models, developed primarily for global applications, were recalibrated using the field and UAV-LS data to better reflect West African forest structural properties. The integration of these datasets allowed for the correction of biases inherent in broad-scale models, particularly for complex mosaics of savannahs, woodlands, and tropical forests. Validated against the field and UAV-LS benchmarks, the refined GEDI models were then applied to generate wall-to-wall AGBD estimates across the region.

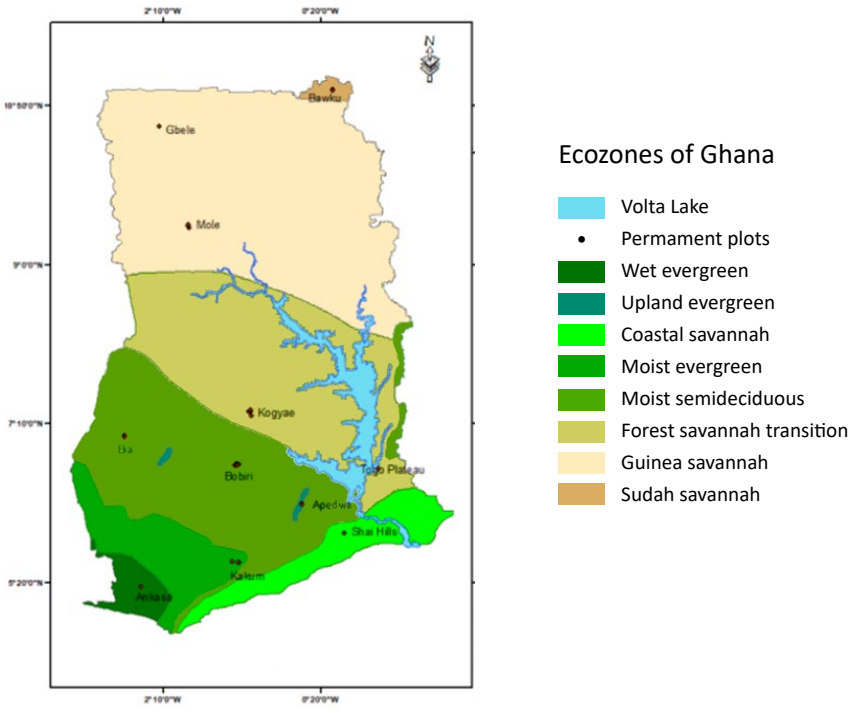
2.1. Field data collection

2.1.1 Study areas

• *The Ankasa Conservation Area (approx. 5°10′ to 5°20′ north, 2°28′ to 2°44′ west)*

It lies in Elubo, in the southwest of Ghana close to the border with Côte d'Ivoire. It is located in the wet evergreen forest type of Ghana. Mean annual rainfall exceeds 2000 mm in the wet evergreen forest type. Mean monthly temperature ranges 24–28 °C. Relative humidity is generally high throughout the year, being about 91 percent during the night and falling to 75 percent in early afternoon (Addo-Danso *et al.*, 2018; Moore *et al.*, 2018). The site has three of the permanent sampling plots (PSPs) of the Global Ecosystem Monitoring (GEM) network, which were re-measured through this research.

Figure 1. Map of Ghana indicating the location of the PSPs against ecological zones



Notes: Refer to the disclaimer on page ii for the names and boundaries used in this map.
Source: Authors' elaboration, generated by harmonizing information from Appiah et al, (2014) and Kumi et al, (2022).

• *The Bia Conservation Area (approx. 6°53′ to 7°05′ north, 2°31′ to 2°43′ west)*

It falls under both moist semideciduous and the moist evergreen forest types. Mean annual rainfall is 1 500 mm and mean temperature is 28 °C. Three PSPs were established in the moist evergreen portion of the Bia Conservation Area.

• *Kakum National Park (approx. 5°20′ to 5°31′ north, 1°16′ to 1°26′ west)*

It's located in the southern central part of Ghana near the coast. Most of the landscape in the park can be classified under the moist evergreen vegetation type, with part falling under the moist semideciduous type. These are composed of pristine forest immersed in agricultural matrices, including waterlogged dense forest patches with lianas and old-growth forest trees. Rainfall annual regime is bimodal with mean annual rainfall ranging between 1 500 mm and 1 750 mm. The average relative humidity is about 80 percent, while the mean annual temperature ranges 24–27 °C (Morel *et al.*, 2019). In total, four PSPs of 1 ha each were measured in Kakum, which required extending previously measured PSPs of 60 × 60 m, making them fully compliant with the standards of the Red Amazónica de Inventarios Forestales (RAINFOR) protocol (Phillips *et al.,* 2021).

• *Bobiri Forest Reserve (approx. 6°40′ to 6°43′ north, 1°15′ to 1°22′ west)*

It's located in the moist semideciduous forest zone. The annual rainfall ranges 1 200–1 750 mm with a mean annual value of 1 500 mm (Addo-Danso *et al.*, 2018). The average temperature ranges 23–35 °C in February (the hottest month; Moore *et al.*, 2018) and 22–28 °C in August. Relative humidity is 85 percent (Foggie, 1947).

Table 1. Ecological zones and number of PSPs established at each

Ecological zone	Site	Plots
Wet evergreen	Ankasa Conservation Area	3
Moist evergreen	Kakum Conservation Area	4
Upland evergreen	Kakum Conservation Area	3
Moist semideciduous	Bobiri Forest Reserve	6
	Bia Conservation Area	3
Forest-savannah transition	Kogyae Strict Nature Reserve	5
	Togo Plateau Forest Reserve	2
Guinea savannah	Gbele Resource Reserve	2
	Mole National Park	3
Coastal savannah	Shai Hills Resource Reserve	3+1
Sudan savannah	Upper Tamne Forest Reserve	3
Total		**37+1**

Note: The +1 in the coastal savannah is the result of the establishment of a 100 × 20 m plot because of the risky nature of the site.

Source: Author's own elaboration.

• *Shai Hills Resource Reserve (approx. 5°51′ to 5°58′ north, 0°02′ to 0°05′ east)*

It's one of the smallest protected areas in Ghana. It is found in the coastal savannah zone and located on the Accra Plains in southern Ghana. It is thus at the western end of the Dahomey Gap, an area of low rainfall where the West African coastal rainforest belt is interrupted and replaced by low grass and savannah (Hall & Swaine, 1981; Dakwa & Yeboah, 2009). The reserve is predominantly dry evergreen savannah interspersed with short trees and shrubs. The annual rainfall ranges 760–980 mm, with a mean of 900 mm. Average daily temperature ranges 25–28 °C. Four PSPs were established, and a previous PSP, which could not be extended from its 0.25 ha size, was abandoned to comply with the standards of the RAINFOR protocol (Phillips *et al.*, 2021).

• *The Kogyae Strict Nature Reserve (approx. 7°09′ to 7°20′ north, 0°59′ to 1°13′ west)*

It's a protected area located in the northeastern part of the Ashanti Region in central Ghana. Kogyae experiences a bimodal annual rainfall distribution with high precipitation periods from March to July and from September to October (McSweeney et al., 2010). The mean annual rainfall is approximately 1 200 mm and the mean annual temperature is 26.4 °C, with minimal variation in temperature over the year (Addo-Danso *et al.*, 2018; Moore *et al.*, 2018). In Kogyae there were five existing GEM PSPs, which were reassessed in this campaign.

• *Togo Plateau Forest Reserve (approx. 7°13′ to 7°20′ north, 0°20′ to 0°27′ east)*

It's the largest reserve in the Volta and Oti regions. It lies within the dry semideciduous forest of the forest-savannah transitional zone (Hall & Swaine, 1981). It is a mountainous area with elevation between 250 m and 2 680 m above sea level. The mean annual rainfall is about 1 500 mm. There is a rather short dry season, characterized by cool dry northeast trade winds from early December to mid-March. Temperatures vary between 22 °C and 34 °C (Hall & Swaine, 1981). FORIG established two 1 ha plots in the Togo plateau.

• *Apedwa Forest Reserve (approx. 6°07′ to 6°09′ north, 0°31′ to 0°08′ west)*

It's a 410 ha Global Significant Biodiversity Area site classified as an upland evergreen forest because of the presence of isolated hills with elevation between 500 m and 750 m above sea level. Average monthly temperatures range 24–29 °C. The rainfall of the area is bimodal, with mean annual rainfall ranging 1 200–1 600 mm (Hall & Swaine, 1981). Three PSPs were established in Apedwa.

• *The Mole National Park (approx. 9°13′ to 10°05′ north, 1°17′ to 2°13′ west)*

It's Ghana's first and largest protected area. It is located in the Guinea savannah vegetation zone of the Savannah Region of Ghana. Average annual rainfall is 1 100 mm. With a mean monthly temperature of 27 °C, temperatures are generally highest in March and April (the dry season) and lowest in December and January (Wildlife Division, 2018). Three PSPs of 1 ha each were measured in Mole, which required both extending previously measured PSPs of 60 × 60 m, making them fully compliant with the standards of the RAINFOR protocol (Phillips *et al.*, 2021) and abandoning a previous PSP which could not be extended.

• *The Gbele Resource Reserve (approx. 10°22′ to 10°44′ north, 2°02′ to 2°18′ west)*

It's the largest forest reserve in the Upper West Region of Ghana. It lies within the extreme Guinea savannah vegetation zone and is the reserve closest to Burkina Faso. Mean annual rainfall ranges

between 950 mm and 1 050 mm (Wildlife Division, 2018). The mean monthly temperature ranges 21–32 °C. Temperatures rise to 42 °C in March, just before the onset of the rainy season, and fall to their minimum (12 °C) in December during the Harmattan, which is brought by the northeast trade winds (Ghana Statistical Service, 2014). Two 1 ha PSPs were established in Gbele.

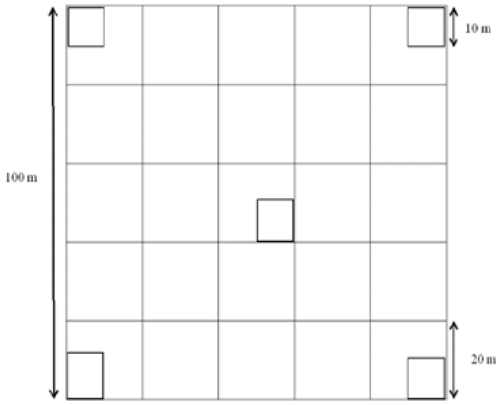
• *The Upper Tamne Forest Reserve in the Bawku Municipality (approx. 10°59′ to 11°02′ north, 0°11′ to 0°12′ west)*

It's located in the Upper East Region of Ghana and lies within the Sudan savannah vegetation type, very close to the borders with Burkina Faso and Togo. Mean annual rainfall is 600–1000 mm and average temperature ranges 26.4–33.3 °C (Asamoah *et al*., 2020). Three existing 60 × 60 m plots were expanded to 1 ha and reassessed in the current campaign. Three PSPs of 1 ha each were measured in Bawku, which required extending previously measured PSPs of 60 × 60 m, making them fully compliant with the standards of the RAINFOR protocol (Phillips *et al.*, 2021).

2.1.2 Permanent sampling plots

Between December 2022 and January 2023, 37 PSPs of 100 × 100 m were inventoried, with all data collection based on the RAINFOR protocol for studying carbon stocks in PSPs (Phillips *et al*., 2021), and they have been established as part of a long-term research project for the GEM network. These were selected to represent the dominant ecoclimatic gradients of West Africa (excluding the Sahel savannah). The number of sampling plots for the various ecological zones and sites is presented in **Table 1**, and the design of the various PSP sites is shown in **Figure 2**. These plots were located across eight ecological zones in Ghana (Hall & Swaine, 1981), including wet evergreen forests, moist evergreen forests, moist semideciduous forests, coastal savannahs, the forest-savannah transitional zone, upland evergreen forests, Guinea savannahs, and Sudan savannahs (**Table 1**). The inventory involved the assessment of existing PSPs and the establishment of new plots in ecoclimatic zones that lacked PSPs at the start of the project. After setting and monitoring of all these plots, a tree-level database was developed, and the biomass and carbon stocks that derived from the data were analysed to represent the foundational dataset for validation later. Following the RAINFOR protocol (Phillips *et al.*, 2021), the 1 ha plots were apportioned into 25 subplots of 20 × 20 m each to aid the mensuration (**Figure 2**). All trees, woody vines (lianas), palms and other hemi-epiphytes with size greater than 10 cm diameter at breast height (d, in cm, 1.3 m above the ground) were inventoried using a calliper. For trees with buttresses, diameters were measured 30 cm above the top of the buttresses (Marthews *et al.*, 2014), using a ladder to climb to the point of measurement. Five smaller plots of 10 × 10 m were established at the four corners and in middle of the 1.0 ha plot (**Figure 2**). 10 m plots were used to measure trees, lianas and hemi-epiphytes with d of 2–10 cm. Treetop heights were measured using a laser range finder for a selection of trees, representing all the present diameter classes, which were used to model the height of the remaining trees on that same plot (Valbuena *et al.*, 2016). The 20 × 20 m grid was employed to aid the exact X-Y coordinates of each tree, and to record the species, functional group, and conservation status of each.

Figure 2. Schematic representation of the layout of a typical 1 ha (100 × 100 m) plot for the inventory of tropical forests based on the RAINFOR protocol (Phillips *et al.*, 2021)



Source: Author's own elaboration.

2.1.3 Coarse woody debris

A combination of a line transect and plot technique was adopted for the sampling of coarse woody debris (CWD). A 2 m wide diagonal on both sides was established in each subplot. Within the 2 m strip, the length and diameters at both ends of all fallen woody materials ≥ 2 and <10 cm were measured. Similarly, the entire plot was assessed for fallen deadwood. Decomposition classes were assigned to measured deadwood materials: sound, intermediate and rotten. Samples of decomposition categories were placed in ziplock bags and taken to the lab for further analysis to determine wood density. The volume of downed deadwood was calculated using the truncated cone formula, by considering the diameter measured at both ends and the length. To estimate the wood density of CWD, sampled individual wood pieces were placed into a graduated water flask to determine their volume, and then these same samples were oven dried at 105 °C for 48 hours and their dry weight was measured. Different wood density values were associated with each decomposition class.

2.1.4 Estimating above-ground biomass density

Above-ground biomass of individual trees (agb in kg) in each subplot was calculated using an allometric equation by Chave *et al.* (2014) for tropical forest stands and by Aabeyir *et al.* (2020) for the savannahs. Phytomass of lianas was predicted using the equation developed by Schnitzer, Rutishauser and Aguilar (2008), and other specific equations were employed for palms. Wood density (ρ in g/cm3) values were obtained from Djagbletey *et al.* (2020), Zanne *et al.* (2009) and the Wood Density Database (Carsan *et al.*, 2012). Whenever there was more than one wood density value available for any given species, the average was used. For standing dead trees, wood density of the "sound" category of the CWD was used. Treetop heights (h, in m) were modelled from the ones measured (Valbuena *et al.*, 2016), selecting the best model form according to lowest root mean square error (RMSE) with high efficiency and negligible bias, among several three-parameter model forms: Chapman-Richard, Gompertz, Hossfeldt, Lundqvist-Korf, logistic function, three-parameter exponential, and monomolecular (Mehtätalo & Lappi, 2020). The pantropical biomass model employed for standing living trees in forests (Chave *et al.*, 2014) was:

$$agb=0.0673(\rho d^2 h)^{0.976}$$

For trees in the savannah zones, agb (Aabeyir *et al.*, 2020) was calculated as:

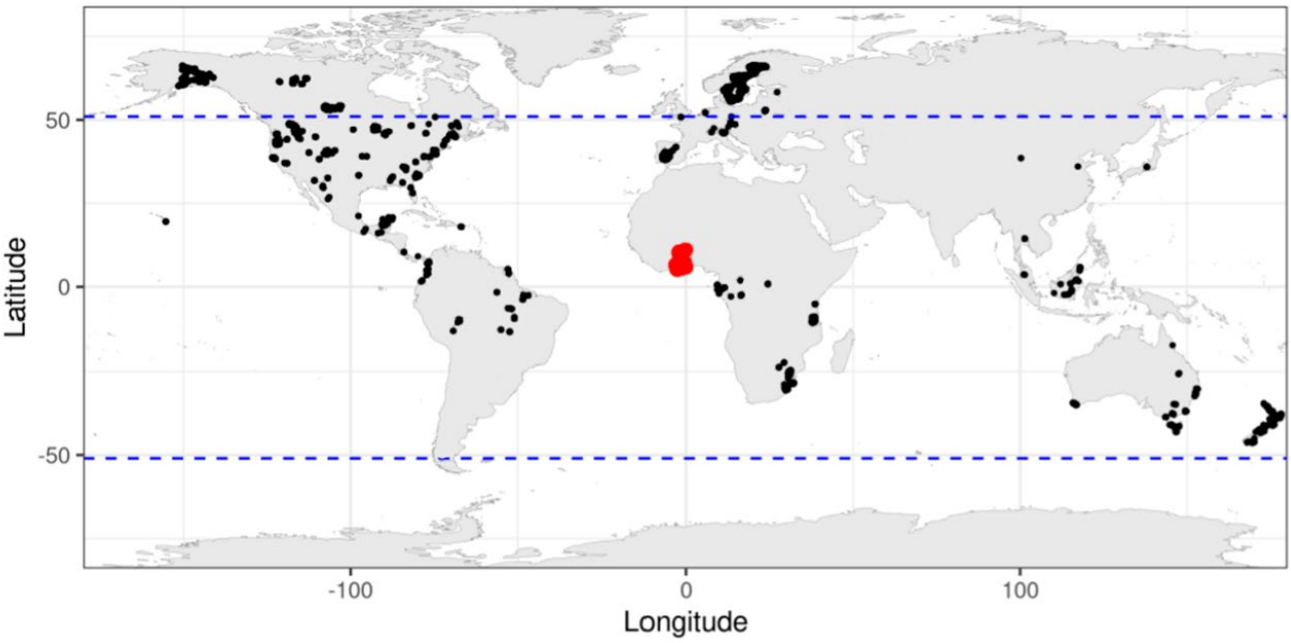
$$agb=0.0580(\rho d^2 h)^{0.999}$$

To estimate the mass of the standing dead trees, we deducted a foliage proportion of 6.25 percent calculated by Henry *et al.* (2010). For the lianas we employed this relationship by Addo-Fordjour and Rahmad (2013):

$$agb=1.643+1.77d$$

After field data were quality checked to correct any errors, hectare expansion factors (the ratio of the area of a plot to a hectare) were used to calculate total AGBD (AGBD, in mg/ha) at each of the 37 plots. To relate the field data with GEDI footprint data, tree-level calculations of agb were aggregated at the 20 m subplot level to estimate AGBD at the scale that provided the best possible spatial match to GEDI LiDAR waveform footprints. After quality assurance and quality control measures were taken to correct for errors, there were 12 405 trees across all 881 subplots within the 37 PSPs, which were all imported to the GEDI Forest Structure and Biomass Database (FSBD) and translated to a common set of geolocated tree- and plot-level observations (**Figure 3**). The distribution of AGBD calculations at the 20 × 20 m subplot and GEDI footprint scales are shown in **Figure 4**, the latter comparing the AGBD values in Ghana against the global GEDI FSBD values.

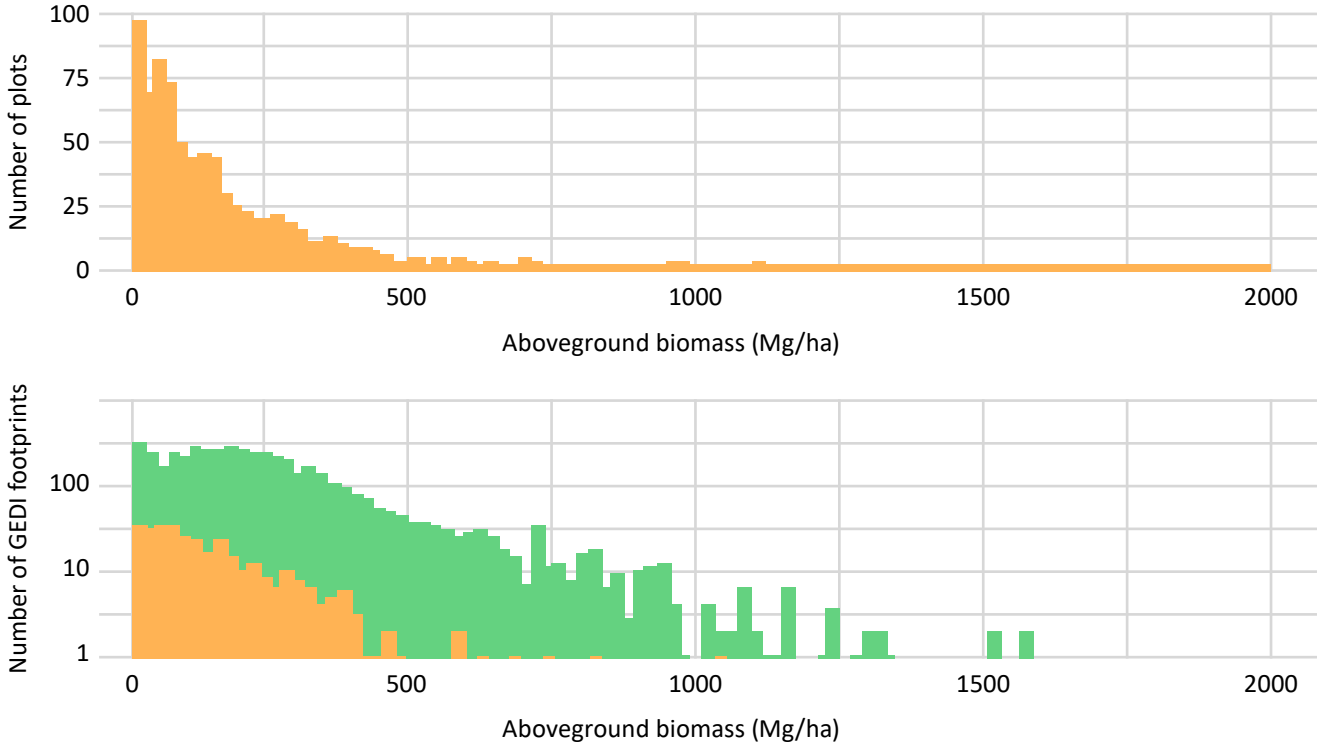
Figure 3. Locations of sites from the data acquired in Ghana through this research (red) relative to all sites in the GEDI FSBD (black)



Note: Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Duncanson, L., Leitold, V., Minor, R., Adu-Bredu, S., Aguirre Gutierrez, J., Armston, J., Dannunzio, R., Garcia Perez, J., Hunka, N., Kellner, J.R., Tavani, R., & Valbuena, R. 2025. Revised GEDI-based Aboveground Biomass Density Predictions for West Africa. (Version 1). ORNL Distributed Active Archive Center.

Figure 4. Distribution of at the 20 × 20 m subplot scale from the present research in Ghana and at the 25 m diameter scale of the GEDI footprint



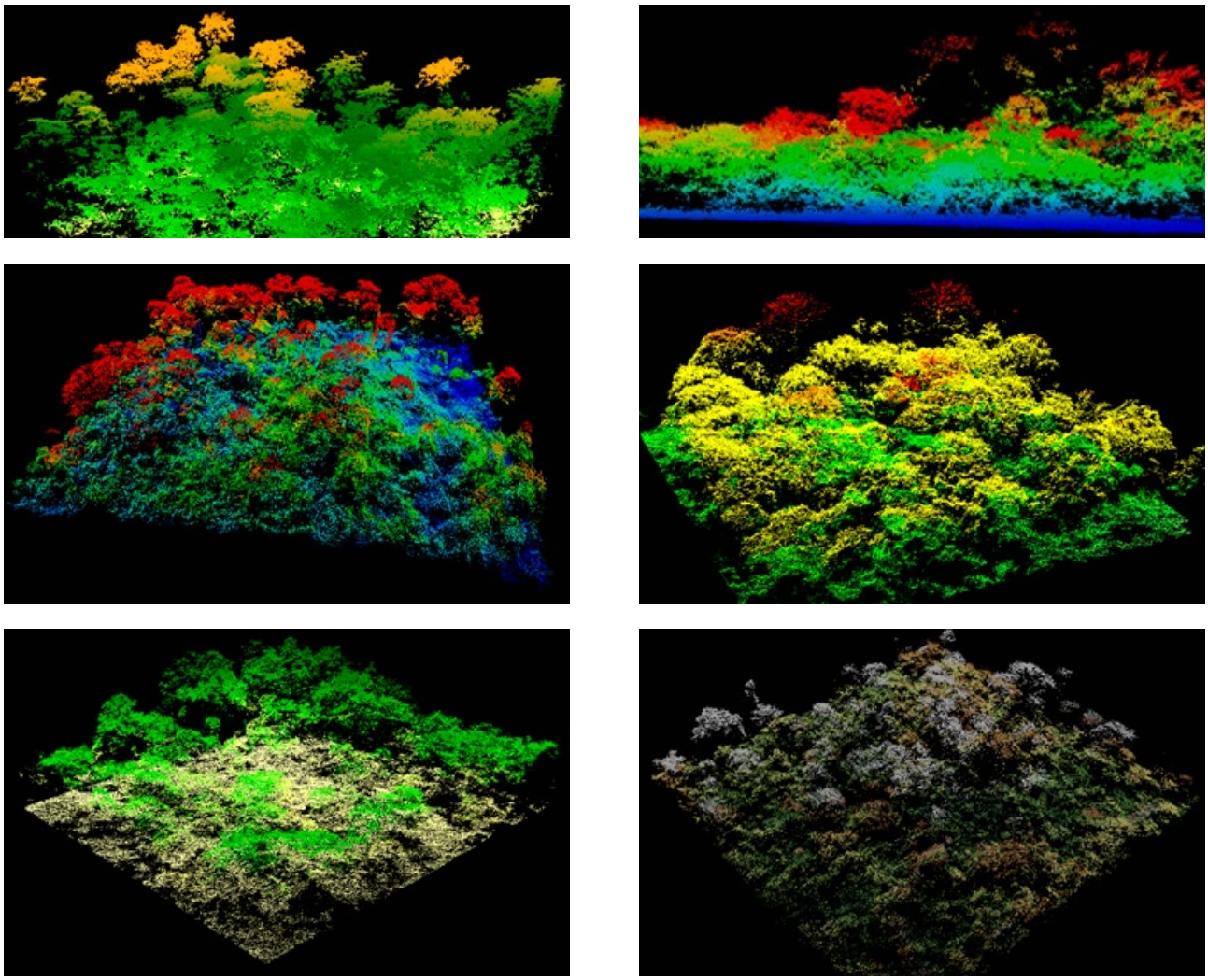
Note: Data from this present research in Ghana (red) are shown relative to all sites in the GEDI FSBD (grey).

Source: Author's own elaboration.

2.2. Unmanned aerial vehicle laser scanning data collection

To bridge the scale gap between field measurements and GEDI's 25 m footprints, UAV-LS was deployed over each plot, capturing high-resolution three-dimensiona l forest structure. This intermediate-scale data enabled precise alignment with GEDI waveforms while accounting for spatial heterogeneity in forest structure. Twenty-five of the field plots were hence revisited with a UAV-LS system, which obtained detailed three-dimensional information about the vertical structure and the position of the ground (Valbuena *et al.*, 2020). Drone surveys were carried out between December 2022 and January 2023, that is, at the end of one of the rainy seasons in Ghana, increasing the chances for good weather. Data were collected from a UAV-LS system. The drone was a Trinity F90+ (Quantum Systems, 2025) equipped with a LiDAR sensor Q240 (YellowScan, 2025) acquiring positional data at a nominal scanning frequency of 240 000 pulses per second. To ensure optimal positional and measurement accuracy, the system combined a global navigation satellite system (GNSS) and an inertial navigation system (INS) using postprocessing kinematic techniques. The INS component, an Applanix APX15 (Trimble, 2025a), was integrated into the UAV-LS system, while the GNSS involved a survey-grade external antenna TDC600 (Trimble, 2025b). Quantum3D software facilitated UAV-LS mission planning, which was further supported by very-high-resolution PlanetLabs (2025) imagery to identify preliminary plot locations and potential UAV-LS launch sites. Ultimately, fieldwork constraints limited the number of UAV-LS

Figure 5. Examples of resulting point clouds from the UAV-LS campaign



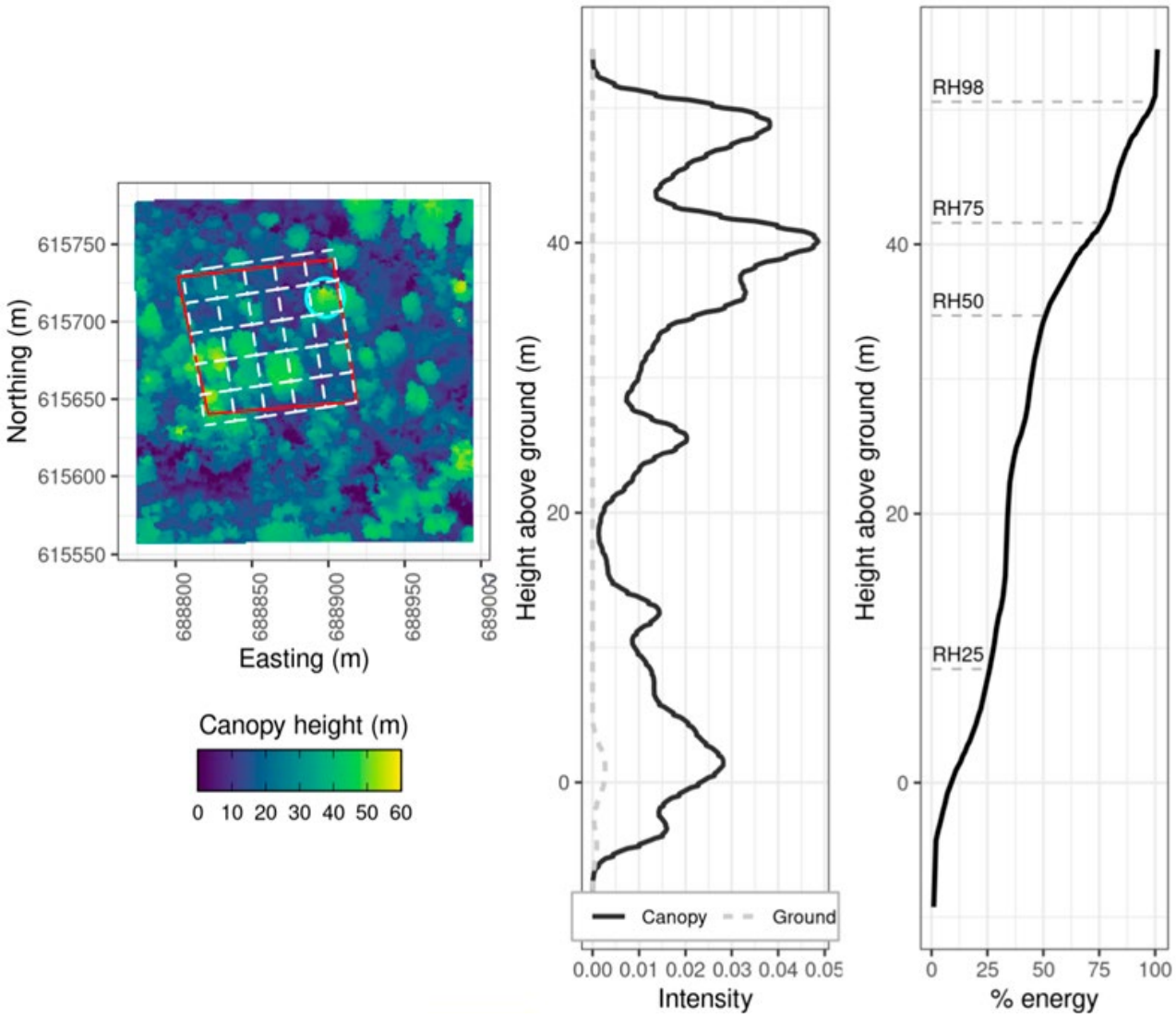
Source: Author's own elaboration.

plots surveyed to 25 of the initially planned 37 PSPs. The flying height was kept as close to the vegetation as possible, with a maximum of 120 m above ground level, resulting in approximate scanning densities of 100 pulses per square metre. From the resulting point clouds (**Figure 5**), customary Digital Terrain Models and Canopy Height Models were generated (Fischer *et al.,* 2024). The digital terrain model enables calculation of heights above ground for all laser scanning point data (Axelsson, 1999).

2.3. GEDI waveform simulation and modelling

The ALS point cloud data were used to simulate GEDI waveforms coincident with the in situ field inventory data (**Figure 5**). The simulated waveforms allowed the use of data from the PSPs to recalibrate the global GEDI model for AGBD (Duncanson *et al.*, 2022, Dubayah *et al.*, 2023). The GEDI waveform simulator has been validated across a range of forest types and ALS instruments using measured waveforms from NASA's Land, Vegetation and Ice Sensor (Hancock *et al.*, 2019).

Figure 6. Simulated GEDI footprints within plot KCA-02

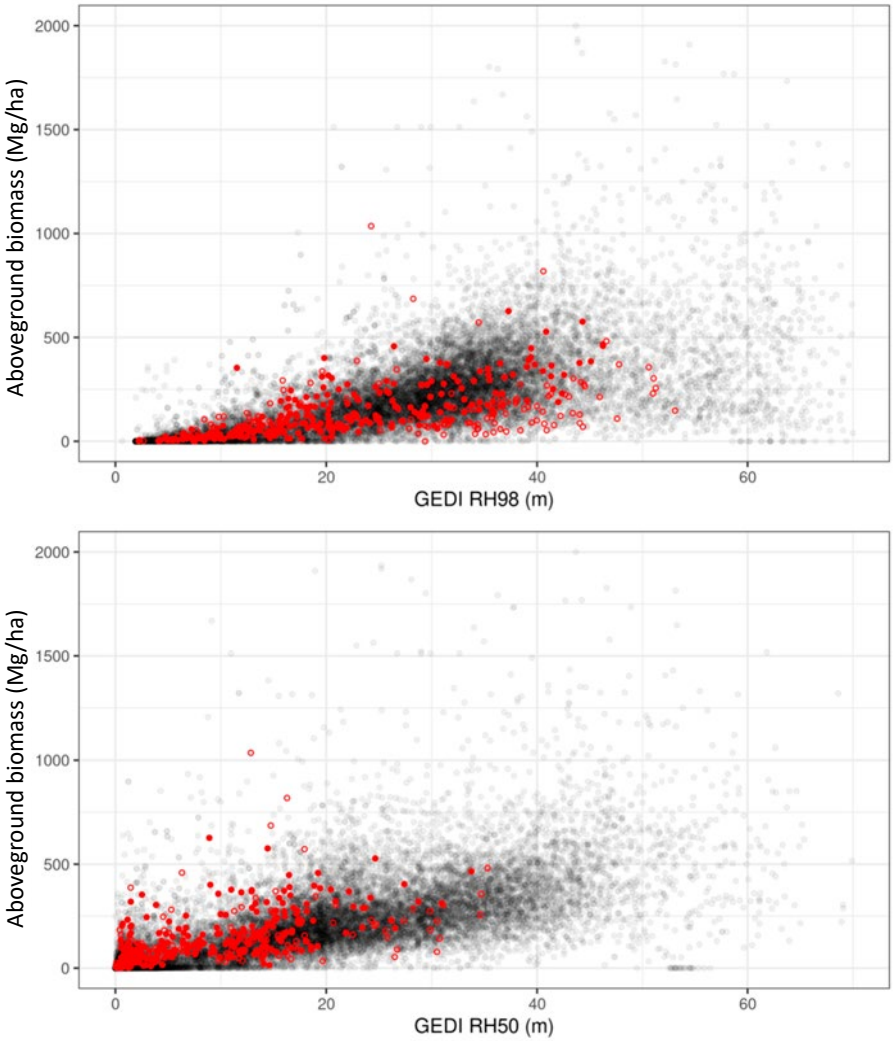


Note: Simulated GEDI footprints within plot KCA-02. The plot area is outlined in solid red lines, and subplots are outlined in dashed white lines. The UAV-LS Canopy Height Model is visualized in the background. The vertical canopy profile for one simulated GEDI footprint, in cyan, is shown on the right. The canopy profile shows the LiDAR waveform simulated from UAV-LS (centre) and RH metrics (0–98th percentiles) (right).

Source: Author's own elaboration.

Figure 6 illustrates an example of a simulated waveform and derived relative height (RH) metrics. Relationships between RH metrics and the in situ AGBD estimates are shown in **Figure 7**, including a comparison with the entire GEDI FSBD, which gives good quality control means for the data acquired in Ghana for this research project. The quality control at the modelling stage reduced the effective number of usable plots from 25 to 17.

Figure 7. RH metric versus AGBD at the 25 m scale of the GEDI footprint relative to all sites in the GEDI FSBD



Note: RH metric (above: 98th percentile, below: 50th percentile) versus AGBD at the 25 m scale of the GEDI footprint (red) relative to all sites in the GEDI FSBD (grey). Open red points will be filtered out of calibration models .

Source: Duncanson, L., Leitold, V., Minor, R., Adu-Bredu, S., Aguirre Gutierrez, J., Armston, J., Dannunzio, R., Garcia Perez, J., Hunka, N., Kellner, J.R., Tavani, R., & Valbuena, R. 2025. Revised GEDI-based Aboveground Biomass Density Predictions for West Africa. (Version 1). ORNL Distributed Active Archive Center.

2.4. Inference

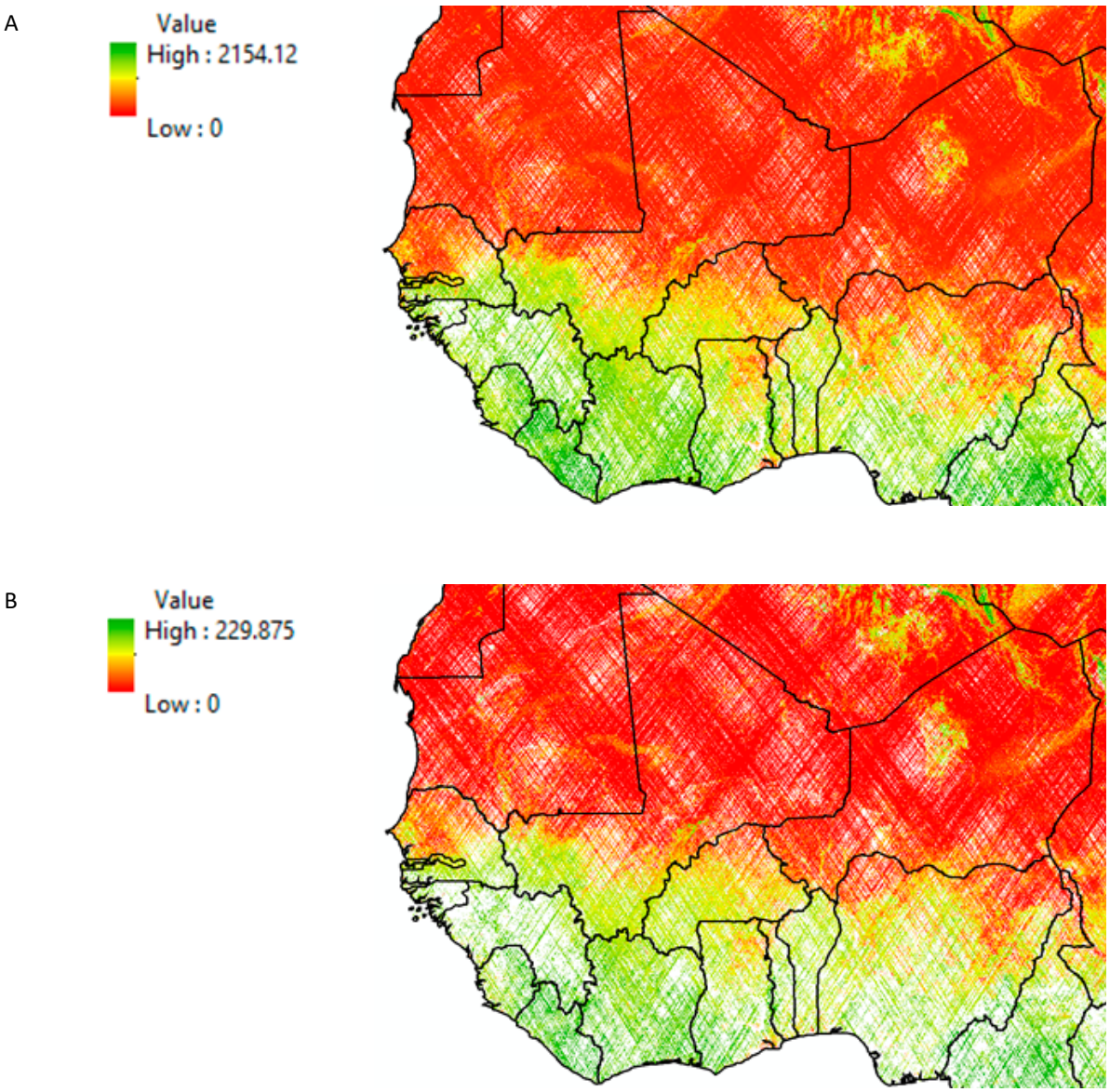
The statistically rigorous use of GEDI data for national reporting follows a generalized hierarchical model-based (GHMB) inferential framework, which requires the direct use of GEDI pulse data (Dubayah *et al.*, 2022). It is also possible to use gridded GEDI products (raster format) using a conservative approach in terms of the uncertainties delivered. These can be particularly useful for countries where these GEDI products have been regionally calibrated, as in the case of Ghana for this project, for which one can compare how calculation may change before or after regional calibration. The approach would follow McRoberts *et al.* (2019) and effectively applies a hybrid-

based level of hierarchy to the GHMB inference already implemented in the GEDI gridded product, in which the total standard error is defined

$$SE = SE^{des} + SE^{mod}$$

where SE^{des} could be tailored to an existing design for an NFI or using a specific design like random sampling without replacement and SE^{mod} will be collected from the model-based errors calculated via bootstrapping (Dubayah *et al.*, 2023) as delivered in the GEDI gridded product itself (**Figure 8**). To keep the approach simple, other components of variance are considered negligible for the scale of national reporting (McRoberts *et al.,* 2018).

Figure 8. GEDI gridded products at 1 km spatial resolution include estimates for (A) the mean AGBD and (B) pixel-level estimates of the standard error of those means



Note: Refer to the disclaimer on page [ii] for the names and boundaries used in this map.

Source: Author's own elaboration.

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RESULTS

Table 2. Comparison of model fit statistics, predictor variables, and data used for model fits for the three PFTs for the original (Duncanson *et al.*, 2022) and West Africa – specific models

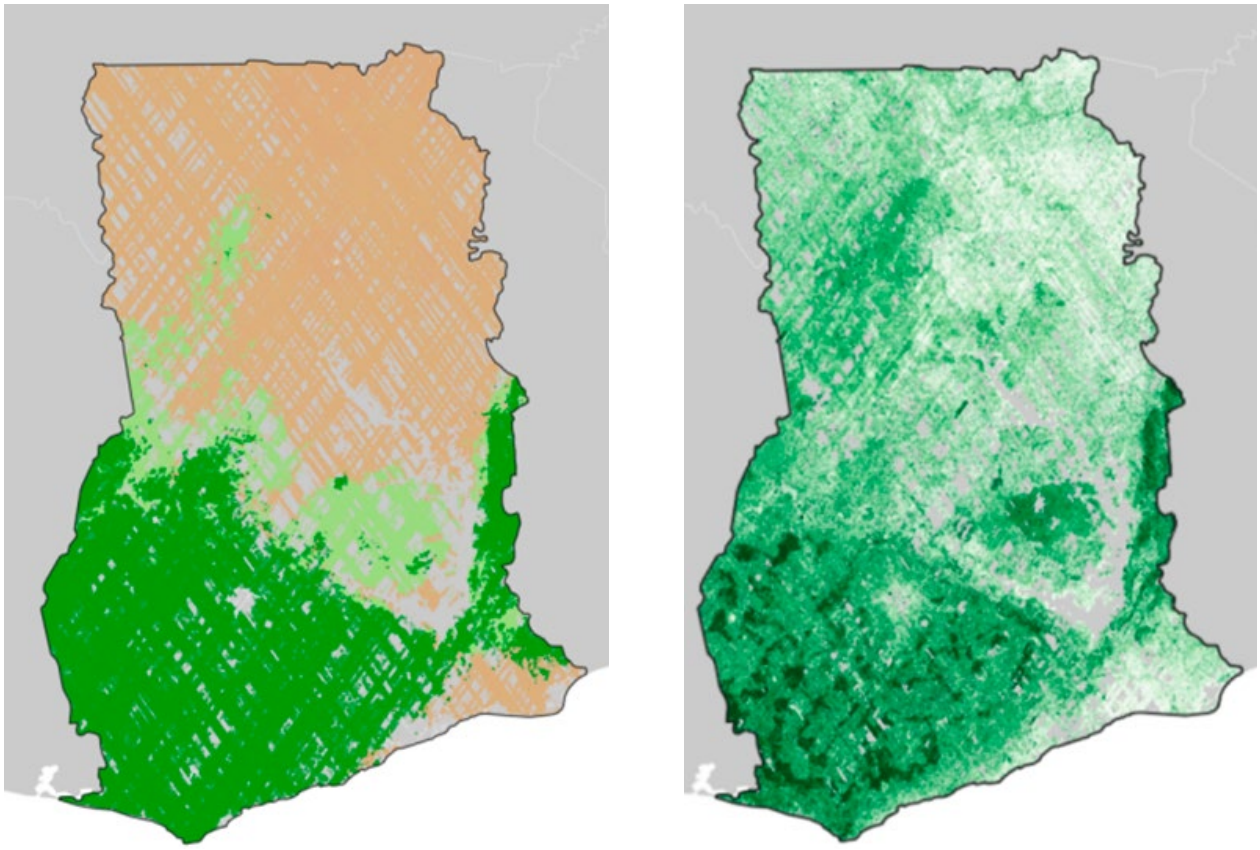
L4A model	PFT	Data for model fit	R^2	RMSE (%)	Bias (Mg/ha)	var1	var2
Original	DBT	United Republic of Tanzania	0.630	57.240	8.410	RH_50	RH_98
Ghana	DBT	Ghana	0.799	54.516	16.691	RH_98	—
Original	EBT	Gabon Democratic Republic of the Congo other EBT Africa	0.640	66.890	15.320	RH_50	RH_98
Ghana	EBT	Ghana	0.799	57.955	60.844	RH_98	—
Original	WGS	Tanzania Mozambique South Africa	0.860	55.390	8.850	RH_98	—
Ghana	WGS	Ghana	0.674	46.097	3.045	RH_98	—

Source: Author's own elaboration.

The final selected models were a suite of linear models predicting ~25 m AGBD as a function of simulated waveform RH metrics from the UAV-LS point clouds, selecting the best fit via cross-validation (Table 2). The modelling was stratified by plant functional type (PFT) derived from a 1 km MODIS product (Figure 8B), following the general practice in the generation of GEDI Level 4 (L4) products. Once the specific models for West Africa were created, a comparison against the original GEDI AGBD products in Ghana was generated.

There were three PFTs for GEDI biomass models in West Africa: deciduous broadleaf trees (DBT), evergreen broadleaf trees (EBT) and woodland, grassland, and savannah or shrubs (WGS). The Ghana training database covered all three of these PFTs and enabled fitting three separate models for Ghana (**Figure 9**). Table 2 shows the statistics of the original models applied to West Africa and the countries where training data were taken, compared to our new GEDI models specifically for West Africa. The resulting models predict AGBD as a function of RH98, that is, a single GEDI height metric. **Figure 10** shows per-stratum comparisons between the original GEDI biomass product (L4A) and the West Africa–specific product. **Figure 11** shows the resulting maps and their spatially explicit differences.

Figure 9. Map of Ghana with actual GEDI pulses

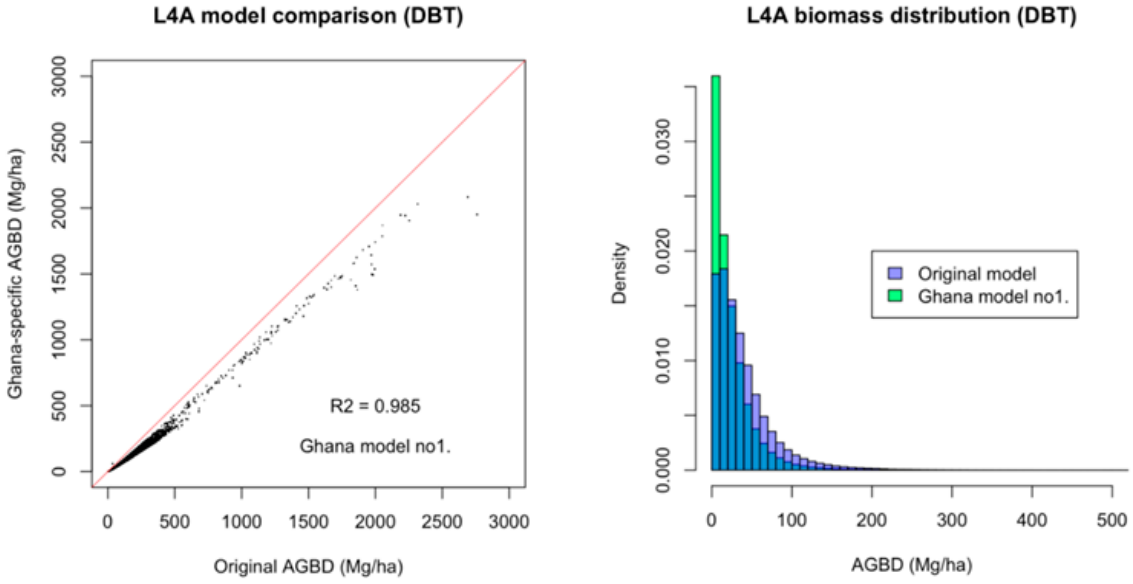


Note: Map of Ghana with actual GEDI pulses showing the parameters involved in the modelling (Table 2), which were the stratification by (A) PFT, and (B) the predictor RH98 metric (in m), which in effect is a measure of the dominant height of Ghana's forests.
Refer to the disclaimer on page [ii] for the names and boundaries used in this map.

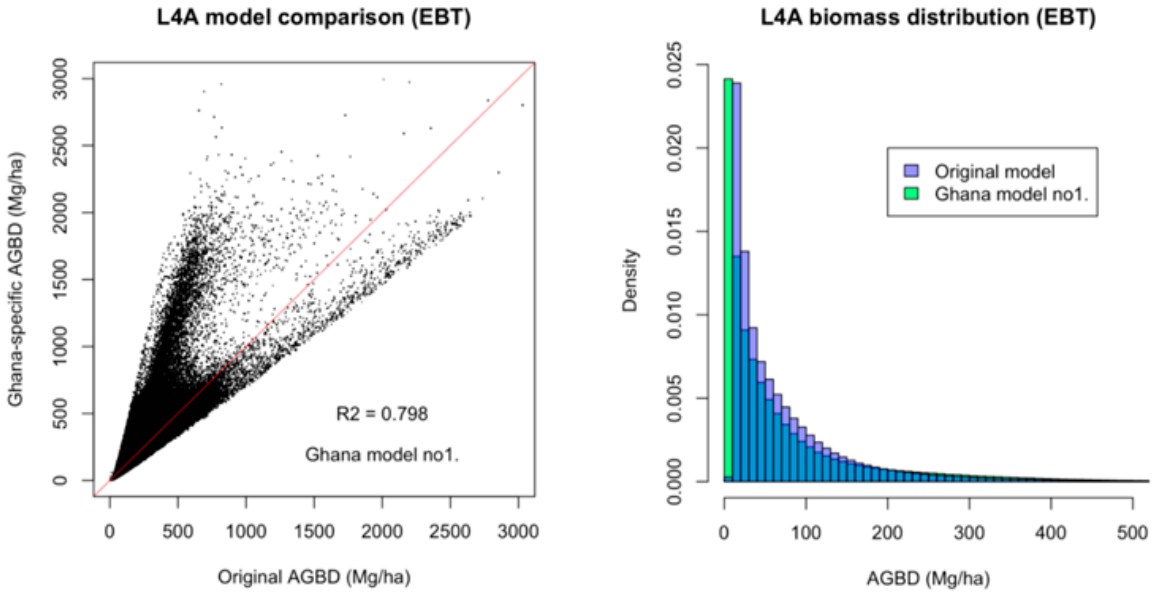
Source: Duncanson, L., Leitold, V., Minor, R., Adu-Bredu, S., Aguirre Gutierrez, J., Armston, J., Dannunzio, R., Garcia Perez, J., Hunka, N., Kellner, J.R., Tavani, R., & Valbuena, R. 2025. Revised GEDI-based Aboveground Biomass Density Predictions for West Africa. (Version 1). ORNL Distributed Active Archive Center.

Figure 10. Comparison of original and Ghana models for each stratum: (A) DBT; (B) EBT

A

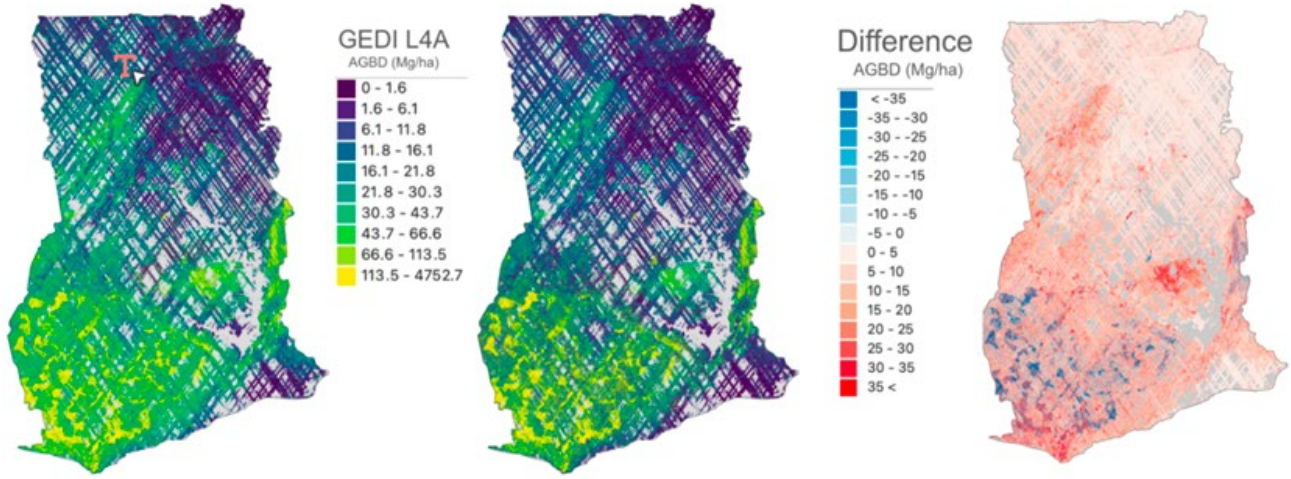


B



Source: Authors' elaboration.

Figure 11. Comparison of new model when applied to on-orbit GEDI (original, new [provisional], and, difference)



Note: The difference is original minus new, so negative values are higher in the new product and positive values are lower in the new product. Generally, the new Ghana-based models produce larger or higher biomass estimates in evergreen tropical forests and lower estimates in deciduous and dryland forests.

Refer to the disclaimer on page [ii] for the names and boundaries used in this map.

Source: Duncanson, L., Leitold, V., Minor, R., Adu-Bredu, S., Aguirre Gutierrez, J., Armston, J., Dannunzio, R., Garcia Perez, J., Hunka, N., Kellner, J.R., Tavani, R., & Valbuena, R. 2025. Revised GEDI-based Aboveground Biomass Density Predictions for West Africa. (Version 1). ORNL Distributed Active Archive Center.

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DISCUSSION

Accurate estimation of forest AGBD is critical to enhance our understanding of carbon cycles (Tian *et al.*, 2022, Ma *et al.*, 2024), to habitat and environmental mapping (Montesano *et al.*, 2013; Quegan *et al.*, 2019), and to guide decision-making in large-scale management of global terrestrial ecosystems in support of climate change mitigation (Herold *et al.*, 2019; Duncanson *et al.*, 2023). GEDI data has been used to provide a first global AGBD map with a pixel resolution of 1 km using LiDAR technology (Duncanson *et al.*, 2022). One of GEDI's primary science objectives is to produce accurate forest structure and biomass products that are useful for policy applications including national reporting. In theory, GEDI biomass data are very well suited to fill gaps in NFIs but only once their accuracy has been nationally or regionally validated, for country versus regional reporting, respectively.

Several sources of uncertainty must be carefully considered when using GEDI data for producing AGBD maps, particularly over heterogeneous canopies. First, the pulse information generated by the GEDI product has been calculated to have a geolocation error of approximately 23.8 m and nominally 10.1 m at 2 and 1 standard deviation, respectively (Beck *et al*., 2021). These errors are expected to be reduced in future releases of GEDI. Second, vegetation height estimates derived from GEDI pulses have been calculated to have RMSE of 2.7 m (Lang *et al.,* 2022). Third, GEDI's AGBD models are calibrated from a suite of contemporaneous field and airborne LiDAR datasets, which do not have balanced representative geographic coverage, and many regions do not have calibration data incorporated into GEDI's models. For these reasons, GEDI's performance for AGBD assessment needs testing prior to uptake for regional applications, especially for using on-the-ground data to reduce the mentioned uncertainties. Given the international importance of the GEDI LiDAR outputs, it is urgent that new datasets be acquired with forest data that can test and improve GEDI's ability to map AGBD in countries and regions from where there is little or no forest data information, especially those that lack an NFI, as is the case for some countries in the West Africa region.

This tiered approach – ground data for validation, UAV-LS for plot-scale structural context and satellite linkage, and GEDI for regional application – ensured that the final AGBD maps balanced accuracy with spatial coverage. By anchoring remote sensing data to field measurements, the methodology addresses key challenges in large-scale biomass mapping, including spatial mismatches between plots and satellite footprints and variability in allometric model appropriateness. The resulting maps may support national and regional climate reporting, while the framework offers a replicable model for other data-scarce regions.

The approach employed in this project can be directly replicated in other areas, and it is scalable to the global level. GEDI can be employed to guide NFI design in countries where an NFI has not been developed yet. However, one limitation is the sampling nature of the GEDI mission, which creates gaps in the landscape (Figs. 7–9), and this cannot be used for mapping unless combined with other satellite sources or spatial mapping methods to fill in gaps. This contingency will soon change thanks to the availability of the new BIOMASS mission. There are also many other potential uses, beyond estimation of AGBD, since these methods are well suited for the development of many other morphological traits of forest ecosystems and can thus be employed for the derivation of global essential biodiversity variables (Valbuena *et al.*, 2020). The methodology is a harmonized approach with the advantages of being cost-effective, helping to reduce the number of field sampling plots required and helping to reduce AGBD uncertainties by leveraging

the use of the newest earth observation data. The methodology allows the interoperability of data at the subregional scale, since in situ data obtained from one country can help in tailoring GEDI estimations to the whole subregion, facilitating comparison and aggregation of data among West African countries. These countrywide biomass maps can support the development of more efficient NFIs and can potentially provide more accurate estimates of carbon emission factors for emissions reporting. It is thus paramount to test this methodology through the present project which, despite not being intended to fully replace data field inventories, can certainly be a suitable time and cost-efficient approach to generate estimations for large areas.

This methodology presents a scalable, harmonized approach for estimating AGBD across large regions, with potential for global replication. While it cannot fully replace traditional field inventories, it offers a cost- and time-efficient alternative, particularly in data-scarce regions, by reducing the sampling intensity needed on the ground. By integrating cutting-edge remote sensing technologies (e.g. UAV-LS and GEDI data), the approach reduces reliance on extensive field plots, minimizes logistical burdens and crew deployment costs, and has been shown to lower uncertainties in biomass estimates (Dubayah *et al.*, 2022; Bullock *et al.* 2023). Importantly, it enables interoperability at subregional scales, facilitating data comparison and aggregation among West African countries, which is a critical step towards consistent carbon reporting. It also facilitates consistent replication: Countries may generate national data on forest biomass more frequently and inexpensively. Beyond AGBD estimation, the framework could support broader applications, such as monitoring forest degradation, biodiversity habitats or carbon sequestration potential, though complementary satellite missions (e.g. ICESat-2, Sentinel, or the recently launched European Space Agency BIOMASS mission) may further enhance robustness. For national implementation, the methodology empowers countries to generate frequent, affordable biomass maps, improving NFI efficiency and refining emission factors for climate commitments. However, challenges remain in ensuring local technical capacity, addressing sensor limitations (e.g. canopy penetration) and validating results across diverse biomes. Despite these limitations, this approach represents a transformative step towards bridging the gap between field measurements and global-scale biomass mapping, offering a pragmatic balance between accuracy and operational feasibility.

DATA RECORDS

Country and regional datasets are available through the website of the project “Global Transformation of Forests for People and Climate: A focus on West Africa”, accessible through:

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